Local Weighting–Based Diagnostics for Bayesian Poststratification

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Are US non-voters becoming more Republican?

Blue Rose research says yes:

“Politically disengaged voters have become much more Republican, And because less-engaged voters swung away from [Democrats], an expanded electorate meant a more Republican electorate.”

(Blue Rose Research 2024)
(major professional pollsters)

***On Data and Democracy* says no:**

“Claims of a decisive pro-Republican shift among the overall non-voting population are not supported by the most reliable, large-scale post-election data currently available.”

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Our contribution

We define "MrP local equivalent weights" (MrPlew) that:

- Are easily computable from MCMC draws and standard software, and
- Provide MrP versions of key diagnostics that motivate calibration weighting.

$\Rightarrow$ **MrPlew provide direct comparisons between MrP and calibration weighting.**

Outline

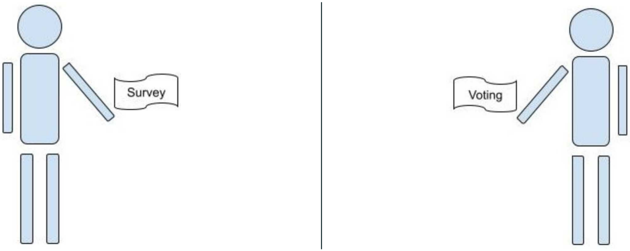
- Introduce the statisical problem and two methods (CW and MrP)
- Describe covariate balance, one of the classical CW diagnostics
- Define MrPlew weights and connect them to covariate balance
- Example of real-world results
- Future directions

The basic problem

We have a survey population, for whom we observe:

- Covariates $\mathbf{x}$ (e.g. race, gender, zip code, age, education level)
- Responses y (e.g. A binary response to "do you support policy such–and–such")

We want the average response in a target population, in which we observe only covariates.



Observe $(\mathbf{x}_i, y_i)$ for $i = 1, \ldots, S$ | Observe $\mathbf{x}_j$ for $j = 1, \ldots, T$

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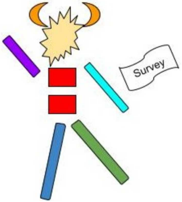

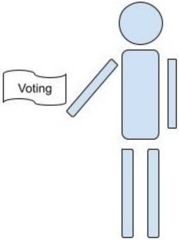

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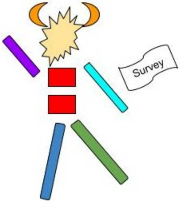

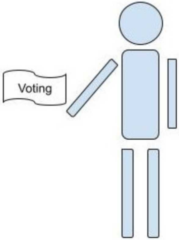

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Our survey results may be biased.

How can we use the covariates to say something about the target responses?

Two approaches

We want $\mu := \frac{1}{T}\sum_{j=1}^{T} y_j$, but don't observe target population y_j.

- Assume $p(y|\mathbf{x})$ is the same in both populations,
- But the distribution of $\mathbf{x}$ may be different in the survey and target.

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Calibration weighting

▶ Choose "calibration weights" w_i
(e.g. raking weights)

Bayesian hierarchical modeling (MrP)

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  - Partial pooling
  - Regressor balance

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$\leftarrow$ (We open this box, providing analogues of all these diagnostics)

What are we weighting for?[1]

We want:

$$\text{Target average response} = \frac{1}{T}\sum_{j=1}^{T} y_j \approx \frac{1}{S}\sum_{i=1}^{S} w_i y_i = \text{Weighted survey average response}$$

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Such weights satisfy "covariate balance" for **x**.

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Such weights satisfy "covariate balance" for $\mathbf{x}$.

You can check covariate balance for any calibration weighting estimator, and any function $f(\mathbf{x})$.

Even more, covariate balance is the criterion for a popular class of calibration weight estimators:

Raking calibration weights

"Raking" selects weights that

- Are as "close as possible" to some reference weights
- Under the constraint that they balance some selected regressors.

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Generalized covariate balance checks

We want to balance $f(\mathbf{x})$ because we think $\mathbb{E}[y|\mathbf{x}]$ might plausibly vary $\propto f(\mathbf{x})$, and want to check whether our estimator can capture this variability.

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Balance–informed sensitivity check (BISC) (informal)

Pick a small δ, and define a *new response variable* $\tilde{y}$ such that

$$\mathbb{E}\left[\tilde{y}|\mathbf{x}\right] = \mathbb{E}\left[y|\mathbf{x}\right] + \delta f(\mathbf{x}).$$

We know the change this is supposed to induce in the target population.

Covariate balance checks whether our estimators produce the same change.

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We know the expected change this perturbation produces in the target distribution:

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Then, check whether your estimator $\hat{\mu}(\cdot)$ produces the same change for observed $\tilde{y}, y$:

$$\underbrace{\hat{\mu}(\tilde{y}) - \hat{\mu}(y)}_{\text{Replace weighted averages with changes in an estimator}} \overset{\text{check}}{\approx} \delta\frac{1}{T}\sum_{j=1}^{T} f(\mathbf{x}_j).$$

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When $\hat{\mu}(\cdot) = \hat{\mu}_{\text{CAL}}(\cdot)$, BISC recovers the standard covariate balance check.

When $\hat{\mu}(\cdot) = \hat{\mu}_{\text{MRP}}(\cdot)$ and δ is small, BISC recovers our proposal.

Generalized covariate balance for MrP

Step one: Construct $\tilde{y}$ such that $\mathbb{E}\left[\tilde{y}|\mathbf{x}\right] = \mathbb{E}\left[y|\mathbf{x}\right] + \delta f(\mathbf{x})$.

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Two possibilities:

- Allow $\tilde{y}$ to take values other than $\{0, 1\}$ and set $\tilde{y} = y + \delta f(\mathbf{x})$, or
- Use an estimate of $\mathbb{E}\left[y|\mathbf{x}\right]$ to draw new binary $\tilde{y}$.

Our approach:

- Use $\tilde{y} = y + \delta f(\mathbf{x})$ to identify problematic "imbalanced" $f(\mathbf{x})$
- Sanity check by generating binary $\tilde{y}$ using $f(\mathbf{x})$ (which is fast and easy)

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Problem: $\hat{\mu}_{\mathrm{MRP}}(\cdot)$ is computed with MCMC.

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MrP Local Equivalent Weights (MrPlew)

Form the approximation

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Computation: The weights are given by weighted averages of posterior covariances[2].

They can be easily computed with standard software[3] **without re–running MCMC**.

[2] **G.**, Broderick, and Jordan 2018.
[3] We use `brms` (Bürkner 2017).

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Theory: We state conditions under which, as $\delta \to 0$, and $N \to \infty$,

- The residual is of lower order than the MrPlew term,
- *Uniformly* over a very wide class of $f(\cdot)$.

Uniformity is the hard part, but this justifies using MrPlew to *identify* problematic $f(\cdot)$.

Builds on earlier work on uniform error bounds for Bernstein–von Mises theorem(–ish) results[2].

[2] **G.** and Broderick 2024; Kasprzak, **G.**, and Broderick 2025.

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If MrP were linear (e.g. if you use OLS instead of hierarchical logistic regression), then

- The residual is zero,
- $\hat{\mu}_{\mathrm{MRP}}(y) = \sum_{i=1}^{S} w_i^{\mathrm{MRP}} y_i$, and so
- $\hat{\mu}_{\mathrm{MRP}}(\tilde{y})$ is a calibration weighting estimator, and w_i^{MRP} are its weights. (Cite Gelman)

In general, MrP is truly nonlinear. The residual is only small when $\tilde{y} \approx y$ (i.e., when $\delta \ll 1$).

Real Data

Analysis of changing names after marriage (based on Alexander (2019))

- **Target population:** ACS survey of US population 2017–2022 (Ruggles et al. 2024))
- **Survey population:** Marital Name Change Survey (Cohen 2019)
- **Respose:** Did the female partner keep their name after marriage?
- For regressors, use bins of age, education, state, and decade married.

Survey observations:	$S = 4,364$
Target observations (rows):	$T = 4,085,282$

Uncorrected survey mean:	$\frac{1}{S}\sum_{i=1}^{S} y_n = 0.462$
Raking:	$\hat{\mu}_{\text{CAL}} = 0.263$
MrP:	$\hat{\mu}_{\text{MRP}} = 0.288 \quad (\text{Post. sd} = 0.0169)$

Figure

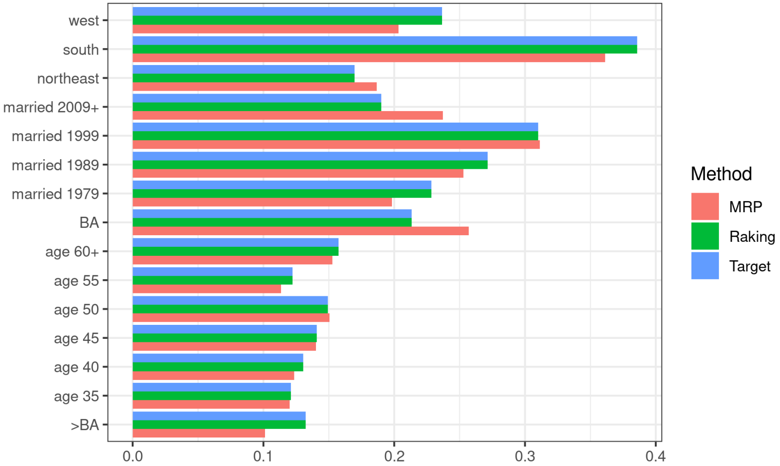


Figure 1: Imbalance plot for primary effects

Figure

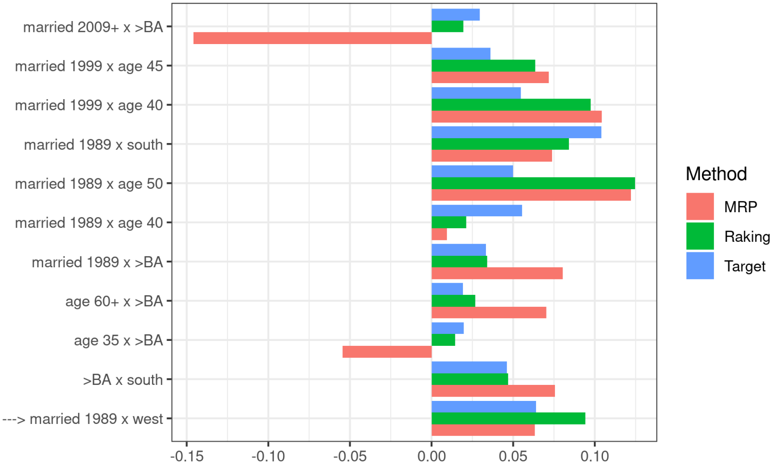


Figure 2: Imbalance plot for select interaction effects

Figure

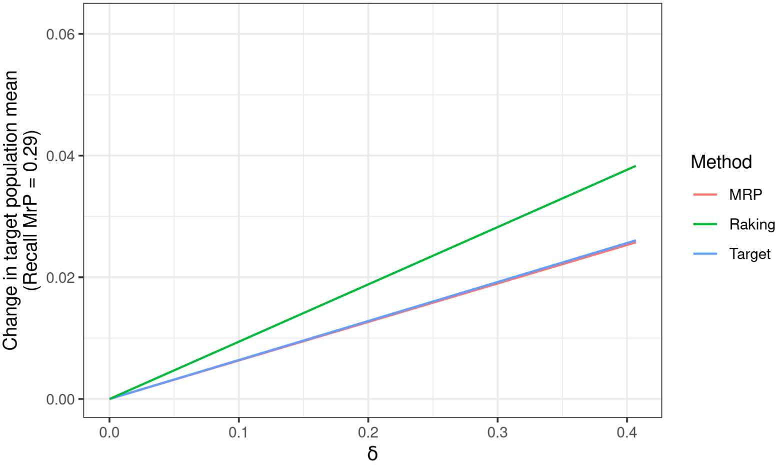


Figure 3: Continuous predictions Alexander

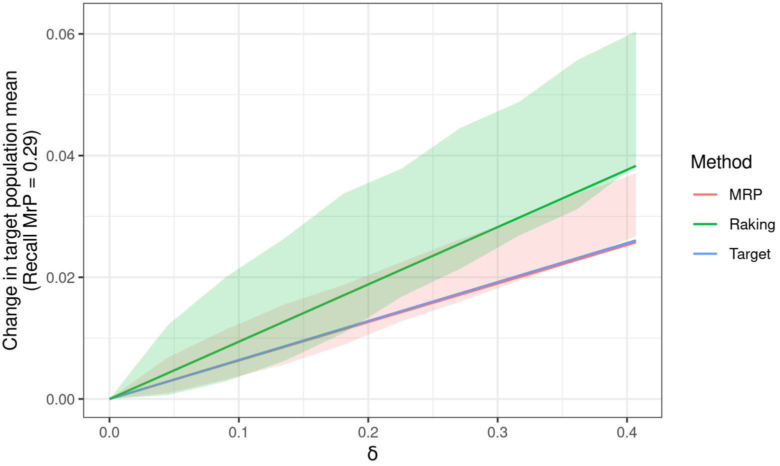
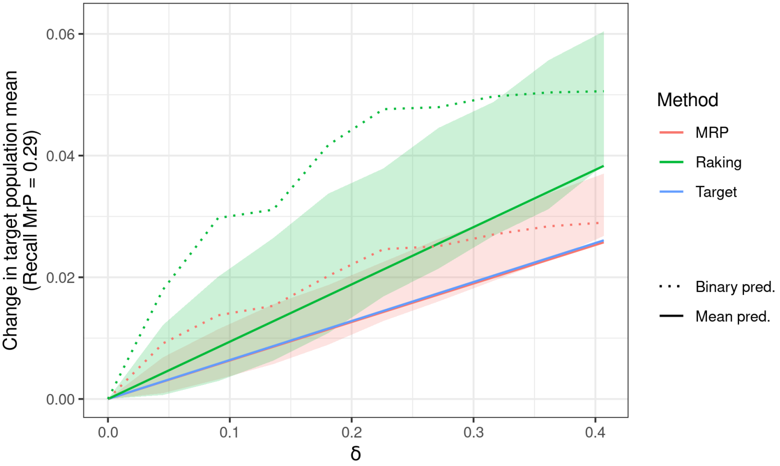


Figure 4: Continuous predictions Alexander



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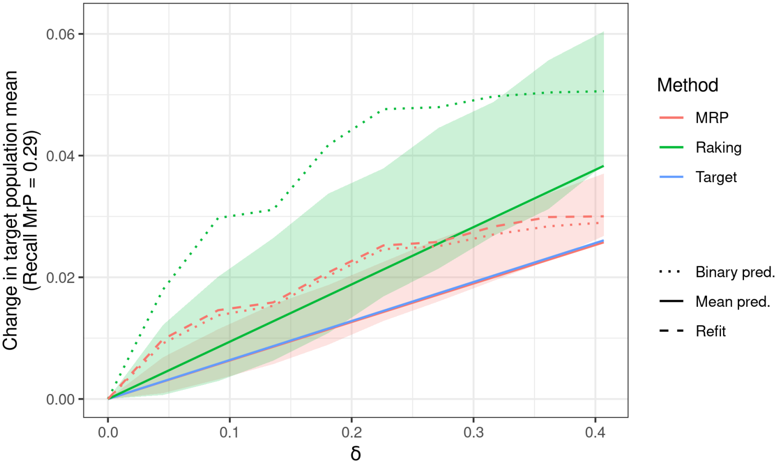

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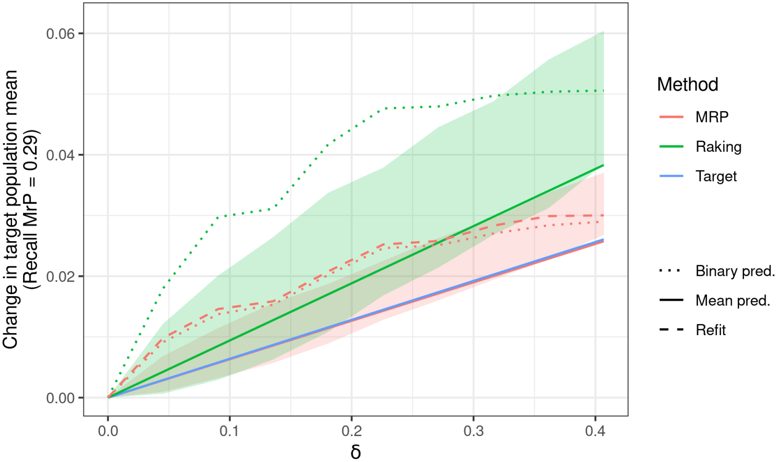

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Running ten MCMC refits: 28 hours Computing approximate weights: 27 seconds

Future work and generalizations

- Instance of a very general class of local consistency checks that generalize classical regression checks (work with Sequoia)
- Versions for GLMMs (work with Vladimir)
- Going beyond classical Bayesian sensitivity (work with Lucas)

References

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